AD-A075 059 UNIVERSITY OF SOUTHERN CALIFORNIA LOS ANGELES DEPT O--ETC F/G 12/2
ESTIMATION AND IDENTIFICATION FOR MODELING DYNAMIC SYSTEMS.(U)
SEP 79 J M MENDEL AFOSR-75-2797

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SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE		READ INSTRUCTIONS BEFORE COMPLETING FORM
1. REPORT NUMBER: AFOSR-TR-79-1043	2. GOVT ACCESSION NO.	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle): ESTIMATION AND IDENTIFICATION FOR MODELING DYNAMIC SYSTEMS		5. TYPE OF REPORT & PERIOD COVERED: Interim rept. 1 Mar 78 - 28 Feb 79
		6. PERFORMING ORG. REPORT NUMBER
7. AUTHOR(s): Jerry M. Mendel		8. CONTRACT OR GRANT NUMBER(s): AFOSR-75-2797
9. PERFORMING ORGANIZATION NAME AND ADDRESS: University of Southern California, Department of Electrical Engineering, Los Angeles, CA 90007		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS: 61102F 2304/A1
11. CONTROLLING OFFICE NAME AND ADDRESS: Air Force Office of Scientific Research/NM, Bolling AFB, Washington, DC 20332		12. REPORT DATE: Sept[redacted]79
		13. NUMBER OF PAGES: 5
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office)		15. SECURITY CLASS. (of this report): UNCLASSIFIED
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

LEVEL

16. DISTRIBUTION STATEMENT (of this Report)

Approved for public release; distribution unlimited.

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

DDC RECEIVED OCT 15 1979 E

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

Systems are modeled in order to understand and explain them better and as a prelude to action. Aircraft dynamics, for example, may be identified so that better designs can be made, or so that adaptive control actions can be taken. Our attention in this continuing study has been directed at aspects of estimation and identification that are connected with system understanding. This study has been aimed at state estimation and parameter identification for a new class of models, causal functional equations, which describe wave propagation in layered media systems. These models are applicable to diverse areas, such as reflection

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20. Abstract continued

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AFOSR-TR- 79-1043

September 1979

ESTIMATION AND IDENTIFICATION FOR

MODELING DYNAMIC SYSTEMS

INTERIM REPORT

AFOSR GRANT 75-2797

March 1, 1978 - February 28, 1979

by

Jerry M. Mendel, Principal Investigator
Research Professor of Electrical Engineering

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I. INTRODUCTION

Systems are modeled in order to understand and explain them better and as a prelude to action. Aircraft dynamics, for example, may be identified so that better designs can be made, or so that adaptive control actions can be taken. Our attention in this continuing study has been directed at aspects of estimation and identification that are connected with system understanding. This study has been aimed at state estimation and parameter identification for a new class of models, causal functional equations, which describe wave propagation in layered media systems. These models are applicable to diverse areas, such as reflection seismology, transmission lines, speech processing, optical thin coatings and EM problems.

II. RESEARCH PROGRESS

1. An important special case of a causal functional equation (CFE), occurs when all one-way travel times are equal. In this case the uniform CFE (UCFE) is

$$\underline{x}(t + \tau) = A\,\underline{x}(t) + \underline{b}\,m(t) \tag{1}$$

with initial values

$$\underline{x}(\sigma) \quad \sigma \in [0, \tau) \triangleq \mathcal{J} \tag{2}$$

Recognizing that any time t ($t \in R$) can be expressed as

$$t = t' + M\tau \text{ where } t' \in \mathcal{J} \text{ and } M \text{ is an integer,} \tag{3}$$

we have shown [1] that the solution to UCFE (1) is

$$\underline{x}\,[t' + (k+1)\tau] = A^{k+1}\,\underline{x}(t') + \sum_{i=0}^{k} A^{k-i}\,m(t' + i\tau) \tag{4}$$

where $t' \in \mathcal{J}$, $k = 0, 1, 2, \ldots$, and $t = t' + (k+1)\tau$.

Equation (4) explicitly shows how the state at any time $t = t' + (k+1)\tau$ depends on an initial condition $\underline{x}(t')$ and the input m. It is of interest to note that $\underline{x}(t)$ depends only on a <u>single element</u> of the initial values $\underline{x}(\sigma)$ ($\sigma \in \mathcal{J}$), namely $\underline{x}(t')$, and a finite number of point values of m. This shows that <u>the solution to the uniform causal functional state equation, although continuous-time in nature, derives its values in a discrete-time fashion for a given fixed value of $t' \in \mathcal{J}$</u>. Of course, there are an uncountable number of points in $\mathcal{J}$; hence <u>we can imagine $\underline{x}(t)$ as being generated by an uncountable number of discrete-time systems</u>.

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When we simulate our results on a digital computer, computations are made every T sec. at discrete time points. Consequently, on a digital computer, $\underline{x}(t)$ is generated by a finite number of discrete-time systems which operate in parallel.

2. We have derived [1] the minimum-variance state estimator for UCFE

$$\underline{x}(t + \tau) = A\, \underline{x}(t) + B\, \underline{m}(t) + \underline{w}(t) \tag{5}$$

and its associated measurement equation

$$\underline{y}(t) = H\, \underline{x}(t) + \underline{n}(t) \tag{6}$$

Let $\hat{\underline{x}}(t)$ denote the minimum-variance estimate of $\underline{x}(t)$ based on all measurements in $\{\underline{y}(\lambda): 0 \leq \lambda \leq t, t \in R\}$. We have shown that for any fixed $t' \in \mathcal{T} = [0,\tau)$, $\hat{\underline{x}}(t)$, where $t = t' + M\tau$ $(M = 1, 2, \ldots)$, is given by the usual discrete-time Kalman filter equations (Ref. A, for example) with t' considered the initial starting time. Of course, to obtain $\hat{\underline{x}}(t)$ for all $t \in R$ we would need an uncountable number of discrete-time Kalman filters; but, imposing a mesh on $\mathcal{T}$ (with grid size equal to data sampling rate) leads to a finite number of Kalman filters which operate in parallel. To the best knowledge of the author this is the first estimation theory result that has led to a natural form of parallel data processing.

3. We have developed an extended minimum-variance estimator for simultaneous estimation of states and parameters (i.e., reflection coefficients) in a UCFE [2]. Simulation results were very disappointing. Reasons for the disappointing results are explained in [2].

4. A simple inverse filter has been developed [4] to suppress multiple reflections from a normal incidence synthetic seismogram. The filter was developed by means of Mendel's Bremmer Series Decomposition [3] and the operator description of state space model of layered media (Ref. B), and is given in terms of z-transforms as

$$\tilde{Y}_1(z) = \frac{Y(z)}{1 - \dfrac{r_0}{1 - r_0^2}\, \dfrac{Y(z)}{M(z)}} \tag{7}$$

In this equation $Y(z)$ is the synthetic seismogram measured by a sensor located on the surface. That sensor receives reflected signals from a layered media due to the normal incident input $M(z)$ applied at the same surface. Parameter r_0 is the reflection coefficient of the surface. $\tilde{Y}_1(z)$ is the output of the filter; it consists of the primary reflection portion of the seismogram and some residual terms; i.e., $\tilde{Y}_1(z) = Y_1(z) + \gamma(z)$. In general, the residual terms $\gamma(z)$ is relatively quite small, and $\tilde{Y}_1(z)$ is a good approximation of $Y_1(z)$. This filter is especially effective when r_0 is relatively large (as in most geophysical situations) in which case $\gamma(z)$ is almost negligible compared with $Y_1(z)$. The filter requires knowledge of the input waveform $M(z)$, surface reflection coefficient, r_0, and measured seismogram $Y(z)$. Observe that (7) represents a <u>nonlinear processing</u> of the seismogram $Y(z)$.

5. We have extended our normal incidence state space model to the non-normal incidence case [5]. The non-normal incidence (NNI) state space model is structurally the same as the normal incidence state space model except that it has twice as many state variables. Because of mode conversion in non-normal incidence, the scalar upgoing and downgoing waves and travel times in each layer as well as reflection and transmission coefficients in each interface are replaced by a vector of upgoing and downgoing waves, a vector of travel times, and matrices of reflection and transmission coefficients.

With this NNI model, we are able to generate synthetic seismograms for a plane wave source, and more importantly, for a two-dimensional point source.

6. We have developed a maximum-likelihood procedure for estimating both the reflection coefficients and one-way travel times [6] for a lossless layered media system in which the layers are non-equally spaced (in time). It uses a state space model as its starting point, one that is more general than (1) since now τ is different for each layer (i.e., $\tau_1 \neq \tau_2 \neq \tau_3 \neq \dots \tau_k \neq \tau$). The only source of uncertainty is measurement noise, $n(t)$. Maximum-likelihood estimates of the parameters are obtained in a <u>layer-recursive</u> format. In essence, first r_1 and τ_1 are determined and layer 1 is stripped away; then r_2 and τ_2 are determined and layer 2 is stripped away; etc. To the best of our

knowledge, this is the first time that both reflection coefficients and travel times have been simultaneously estimated in an optimal manner.

PUBLICATIONS UNDER GRANT 75-2797

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